Northumbria Research Link

Data, Data Everywhere, and Still Too Hard to Link: Insights from User Interactions with Diabetes Apps

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ABSTRACT
For those with chronic conditions, such as Type 1 diabetes, smartphone apps offer the promise of an affordable, convenient, and personalized disease management tool. However, despite significant academic research and commercial development in this area, diabetes apps still show low adoption rates and underwhelming clinical outcomes. Through user-interaction sessions with 16 people with Type 1 diabetes, we provide evidence that commonly used interfaces for diabetes self-management apps, while providing certain benefits, can fail to explicitly address the cognitive and emotional requirements of users. From analysis of these sessions with eight such user interface designs, we report on user requirements, as well as interface benefits, limitations, and then discuss the implications of these findings. Finally, with the goal of improving these apps, we identify 3 questions for designers, and review for each in turn: current shortcomings, relevant approaches, exposed challenges, and potential solutions.

AUTHOR KEYWORDS
Health; chronic conditions; mHealth; apps; quantified self; personal informatics; Internet of Things; digital health.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Successful type 1 diabetes (T1D) management typically requires the careful balancing of multiple medication and lifestyle factors, assisted by frequent interaction with diverse data. The interfaces of mobile health apps aim to support this process through assisting in the discovery of relevant trends and patterns in collected data. However, relatively little is known about how well existing interfaces support specific T1D user requirements such as frequent decision making, extraction of relevant insights from complex data, and emotional coping. In order to investigate these issues, we analyzed 16 mediated sessions in which people with diabetes explored relevant data using typical diabetes smartphone apps.

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Our research focused on the logging or diary paradigm, which has become a de facto mainstay of daily diabetes management smartphone apps, a carry-over from the paper based record book. Such apps currently have two primary mechanisms for assisting in daily self-management: the first in the increased engagement with data caused by the act of logging, and the second in the ability to reflect on and learn from this collected data in order to inform future decisions. These apps typically offer multiple methods of visualizing the same collected data, as well as other functionality such as data sharing, or customizable notifications. These many features can prevent studies focused on general benefits from providing useable evidence as to the effectiveness of individual components [20]. Therefore, systematic and reproducible methods are needed to understand how specific features of differing approaches are respectively succeeding and failing to meet user needs.

To investigate how specific data visualizations assist users with obtaining value from collected data, we populated 8 existing commercial diabetes apps, with a single standardized data set. This enabled systematic within- and across-subject comparisons of interface designs, while at the same time mitigating confounding variables which could have resulted from using personal data. For these reasons while using personal data would be valuable for other purposes, it would have not been optimal for this study. While this research was T1D specific, there is reasonable evidence to suppose that the issues investigated here have wider implications: for mobile health apps for other chronic conditions; and potentially for health, wellness, and data driven lifestyles more generally.

HCI AND DATA INTERACTION FOR HEALTH
In this section we briefly review Human Computer Interaction (HCI) research with implications for the use of mobile and wearable technologies to support cognitive and affective aspects of chronic disease management. Before the smartphone era, Intille [16] proposed a system of ‘just-in-time’ text reminders. A key aspect of this approach, still poorly addressed in current apps, was contextual awareness, emphasizing the need for “*the right message, at the right time, in the right way*.” While [24] investigated how technology can assist with collecting diverse data for conscious

reflection and learning, [1] noted that such HCI research depends on high user motivation and explored how to utilize ‘Mindless Computing’ or the changing of people’s behaviors without their awareness. Of particular interest to our research, [25] proposed a *sensemaking* framework, a cyclical multi-stage model where gaps in understanding lead individuals to construct and test new mental models, which when verified can assist in guiding future actions in a more automatic and therefore sustainable manner.

Quantified Self (QS)

In a non-disease specific context, [22] researched and asserted the utility of collecting personal information as a means of self-discovery, and drew attention to the need to balance the engagement benefits of manual logging with the adoption benefits of automation. Recent QS research has also explored topics relevant to diabetes, such as reasons people abandon self-tracking behaviors [9] and why they stop using wearables [7]. A finding which might be considered by developers of logging apps, [30] found that tracking is largely a short term activity, with study participants primarily using logging apps for short periods as part of a larger goal. As users often have difficulties maintaining app usage, [10] drew attention to the need for designers to plan for re-engaging lapsed users, evolving goals, and their desire to change tools. However, while QS has many methodological and theoretical overlaps with chronic disease management, there are factors that argue for domain specific research. Examples include: the non-elective nature of disease; frequency of treatment decisions; need for continuous monitoring, greater unpredictability of measurements; affective impact of unwanted results due to justifiable fears of health complications; and the critical nature of situated decision-making based on personal data.

Diabetes as a Test Case

The next sections briefly outline the practical, cognitive, and affective pressures on users of mobile health apps for diabetes, and the corresponding requirements they create for designers. To understand why diabetes offers an excellent test case for mobile health interventions, it is useful to consider some of the specific challenges it poses. Diabetes is a serious and prevalent condition with current estimates at over 400 million patients worldwide [36]. T1D, which afflicts 5-10% of those with diabetes, is an autoimmune disease where the body rejects the cells that produce the hormone insulin. There is currently no practical biological cure for T1D, and therefore multiple daily injections of insulin or the wearing of an insulin pump are required to control Blood Glucose (BG) levels. While it can be successfully managed with a carefully controlled lifestyle and insulin, diabetes management remains challenging and a majority of individuals do not achieve recommended guidelines [26].

Dynamic Diabetes Self-Management

Before the advent of practical self-administered BG tests, standard treatment involved a doctor prescribing to the patient a rigid daily schedule of diet, medication, and exercise. However, such inflexible regimes are difficult to maintain among the requirements of normal life [11]. The multitude of hard-to-control and individualized factors that can affect daily insulin requirements (stress, dietary availability, variable hormonal activity, variable insulin sensitivity, etc.) are more likely to be met using a more flexible approach [32], where the patient takes primary responsibility for their daily care, self-adjusting insulin dosages and other factors, and the health care professional takes a supportive role [11].

Cognitive requirements

Cognitively, achieving glycemic stability demands that users continuously make sense of various data in relation to specific contexts in order to determine appropriate actions. For example, determining an insulin dosage might include: carbohydrate content of meal along with its glycemic index, the ratio of carbohydrates to insulin generally required for the user, current BG level, target BG level, and other adjustments for contextual insulin requirements [29].

Affective requirements

Affectively, People with Diabetes (PwD) may routinely experience emotional reactions when interacting with undesired personal diabetes data [18]. This poses design challenges on how best to alert users to important information without causing undue emotional distress that could lead to discouragement, system abandonment, or counterproductive stress.

Diabetes Apps: Approaches and Design Issues

As a final essential piece of context for the study presented here, we review the following aspects of diabetes apps: common features; data visualization paradigms and design issues; current evidence on effectiveness.

Common features

Journaling/monitoring are common feature of diabetes apps [15], with frequent support for the recording of BG level, medication, diet, and physical activity. Responsive adaptive interfaces, and individualized decision support for T1D is a largely unexplored area, although there are indications of progress [13]. The HCI community has contributed to the development of features for diabetes apps, such as flexible attachments for contextual data [34], and the use of digital photography to aid and augment memory [33]. Many popular diabetes apps now include such functionality.

Visualization of personal data and design issues

As understanding complex personal data can be challenging [23], an important aspect of these apps is to help the user in this process. To this end, many of these apps make use of standard graphic visualizations such as plots, graphs, tables, and charts, which are considered to be effective methods for seeing tendencies and discovering correlations [5]. However, there is a lack of specific research on the effectiveness of such techniques for assisting the lay-user in understanding complex multivariate data. Within this medical context, this interaction must be carefully designed, as presentations of data can reinforce biases rather than lead to actual insights [23]. It is not clear that current products are adequate for meeting user needs, as [8] cautions that most available diabetes oriented products are primarily for the collection and visualization of data, and are often difficult for users to employ. While there are many papers that assess the effectiveness of an app [12], usability and the limitations of screen dimensions [21], or describe a participatory design process [2], there is still little available research specifically addressing how mobile UIs support self-management processes through assisting actual users in extracting actionable insights from collected data.

Efficacy and known barriers to adoption

Despite considerable effort in assisting diabetes management with mobile digital informatics tools, and some positive results [35], there are still considerable barriers to long-term adoption [2], and efficacy of apps remains controversial. One study looked at mobile apps for children and young adults with T1D [31], and found only limited evidence for changes in self-efficacy and A1C (an established measure of glycemic average). This study also noted the great difficulty in maintaining longitudinal use of apps, and that PwD tended to stop using diary apps when they felt they had stabilized. The affective nature of interventions must be carefully considered, with [4] noting how tracking could increase feelings of disease burden while [6] questioned the clinical validity of many of these apps. Such inconclusive results suggest the need for further research to better understand the individual components that make up these apps, and how to improve them as tools for supporting better self-management practices.

METHODS FOR THE STUDY

In order to compare the utility of different data visualization paradigms, we initiated and analyzed mediated sessions in which people with diabetes explored pre-collected diabetes data (see "data preparation" section below), These sessions employed 8 representative methods of visualizing data taken from 6 free iOS apps. The visualizations examined were: daily logbook, scatter plot, connected scatter plot, daily logbook w/ graph, pop-up cards, statistics, data table, and pie chart (see Figures 1-8).

Apps included in the Study

Our app selection criteria were designed to address three considerations. Firstly, we prioritized coverage of what our cohort actually uses, by selecting the 3 apps most commonly mentioned in our pilot survey (mySugr, SiDiary, and iBGStar [17]). Following that, apps from the app store were sorted into representative categories to ensure representation of principal UI techniques and paradigms. Finally, we made selections from within the categories, prioritizing free apps of particular research or industry interest: e.g. Bant was developed by a medical center through a participatory design process, with several academic studies on its use; Accu-chek was the centerpiece of a commercial diabetes product eco-system; Diabetik was a patient initiative, crowd funded project. While there are newer UI's, these methods of data visualization are standard and widespread.

Assumptions Guiding Study Design

We did not test usability in regards to entering data, which is a known barrier to adoption [17], as the primary focus of this study was the ability of interaction designs to support *retrospective analysis of collected data*. We pre-entered diabetes data within the chosen apps so that all users would be viewing identical information. While this methodology has the limitation that the data has not come from the individual participant, and therefore lacks personal contextual cues, it also offers the following advantages for our specific study goals which could have been inhibited by the use of actual personal data. We sought to understand a UIs ability to communicate information, as opposed to helping people remember events, which would be a valuable (but different) study question. A standardized data set also limited confounding variables; for example, if one participant had easier to locate patterns or more 'ideal' measurements, this could have complicated comparison between subjects. A common data set also allows a uniform and testable within subject experience across multiple apps, interface elements, and users. Finally, reproducibility is also a benefit of such an approach, as well as providing a convenient method of comparing new UIs against older interfaces. We argue that if users could readily extract significant value from such data, and reported favorably on such interactions, this would suggest that they could do at least as well cognitively with their own data. By contrast, if users struggled to understand or interact with data, or expressed clear concerns for cognitive, affective, or other reasons apart from conventional usability issues, then this might indicate the need to address the underlying interaction paradigms themselves. Hekler et al. [14] note that empirical qualitative research can help to form an evidence-based foundation for future design . While in early planning stages we considered using printouts, we ultimately decided that it was important to use an actual device to test interactions. An iPhone 5s running iOS 9 was mounted into a custom-built lightweight rig that allowed a fixed webcam to record audio and visual interactions. The participant held the phone in one hand naturally, while manipulating the interfaces with the other.

Data Preparation and Procedure

It was originally hypothesized that we could measure the success of an interface, according to time and effort required to locate specific pre-determined insights. To this end, the lead author fabricated diabetes data in consultation with a diabetes care professional. However, it became apparent that such an approach was overly artificial as several participants (P1-P4) noted that the recorded values didn't look authentic, and the act of probing for clearly defined solutions seemed too removed from natural interactions. To correct for these discrepancies, the lead author, a T1 diabetic, recorded 14 days of actual data comprised of blood glucose levels, carbohydrate intake, exercise, and insulin dosages [19]. There were 173 entries recorded into each of the 6 selected apps. This new set was then used from the 5th participant onward. However, these pilot observations on

UIs were generally consistent with later results, we have included these responses. Participants were not notified as to origin of data, to not bias responses. The sessions began with a briefing and a consent form. This was followed by a short profile questionnaire on personal characteristics, product choices, and patterns of diabetes app usage. Participants were then read the interaction procedure, and instructed to 'think aloud' as they used the apps. To increase engagement, it was suggested that participants might role-play that they were advising a newly diagnosed PwD who was showing them personal data or alternately to imagine that the data was their own. A variable length semi-structured user interaction session lasting between 20-65 min. was then conducted. Participants were asked questions such as: *What do you see about the BG control in this period? Would this system help you make better decisions about your diabetes management? How do you feel about this interface? How does this interface make you feel about being diabetic?* The order of the apps presented was random, though due to time limitations and some UIs more quickly reaching saturation of opinion, we chose to focus on interfaces which were receiving richer or more varied responses. This has led to not all interfaces being viewed by all participants, and therefore not all denominators are equivalent. Videos were transcribed, and then coded in Nvivo, according to app, interface type, emotional response (positive, mixed, negative, neutral), and expressed usefulness (helpful, mixed, not helpful). The University ethics board granted human studies approval. There were no financial incentives offered.

Participants

We recruited 16 T1D adults through a Berlin based diabetes and technology Meetup, convenience sampling, and a 1-day Berlin-based T1D event. The inclusion criteria included being T1D, over age 18, and speaking conversational English. Age range was from 25-49 years with a mean age of 34 years. Time since diagnosis ranged from 2-31 years, with a mean of 14. Gender was 5 female, 11 male. Overall, 13/16 participants worked or studied in a diabetes related field, information technology, graphic design or software design, and 9/16 reported post-graduate education. All participants reported they were comfortable with smartphones and 13/16 had previous experience with diabetes diary apps. At the time of the study only 1/16 participants was a current daily user of diabetes logging apps, and three participants stated that they still used diabetes apps on occasion. This rate of diabetes app adoption was in accordance with our earlier pilot research [17], which found insufficient benefits in relation to workload, negative emotional effects, and insufficient integration with existing devices and medical services as barriers to adoption.

FINDINGS (ORGANISED BY 8 VISUAL PARADIGMS)

The following sections report on observations in regard to participants' interactions with the selected interfaces. Reporting on known and easily fixable usability shortcomings such as slow scrolling or insufficient font size, are excluded. In some instances, more than one example of an interface paradigm was tested, and their results have been combined, though due to space limitations, only one interface of each type is pictured. The analyzed benefits and limitations for the selected apps are grouped by the 8 identified interface paradigm as follows: Daily Journal; Daily Logbook with Connected Plot; Non-Connected Scatter Plot; Pop-up cards; Statistics, Data table; Pie chart.

Daily Journal Interface (Fig. 1)

While the daily journal is considered a principal component of diabetes self-management apps, users had mixed response as to the utility of this paradigm for reflection. Participants were, for the most part, capable of retrieving stored data from these interfaces and understanding significance, but many found locating correlations across multiple days or finding deeper insights challenging. As the smartphone based log allows the collection of extensive data, it could be useful for distinct goals, such as recording data before a medial appointment, but appears limited as a daily management tool by itself.

UI Benefits

P7 found the Accu-chek logbook serviceable, stating *"it's very easy to scroll through it forward and see."* and was able to assess a day in a meaningful way, "*…if I had 16.0 one of my tests…I need to take immediate action to bring it down, even 14.0…so having 3.0 is the same, you would have some sugar to bring it back up…"* P7 also emphasized a common theme that such records would be useful for interacting with clinicians, *"very good records of everything …I've got good amount of information to hand off to my doctor"* P9 explained that such apps support recall of specific diabetes relevant data, *"…well I understand what it's saying…on an individual point by point basis …I can understand each one, like time, action, and then amount"*

UI Limitations

Despite benefits for browsing data, it was not clear how useful this function is for situated self-management. P7 when asked if this interface would help with daily diabetes management, stated "*it gives you a lot of information so it has the potential to (help) but the likelihood is, if I put up this data I wouldn't bother to look…so it probably wouldn't help…. I'm a little bit overwhelmed with information."* P12 felt a disconnect from such interfaces, *"it's just about numbers…"* P15 brought up the negative emotional aspects of tracking diabetes, *"…I have a feeling that I have to record everything, so I have actually to track my life every year every hour almost… it's not a good feeling at all…I'm not feeling free…if I track what I'm doing all the time."* And P9 firmly rejected the paradigm, *"I probably wouldn't use something like this, I would just find it frustrating and time consuming and not …providing me what I would want…"*

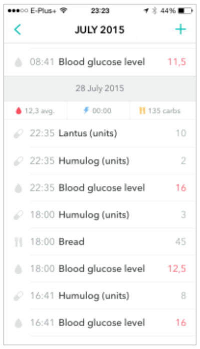

Figure 1 Diabetik Journal / Logbook

Figure 2 mySugr Logbook/ Connected Plot

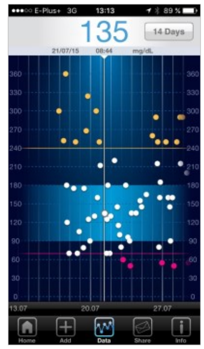

Figure 3 iBGStar Non-connected Plot

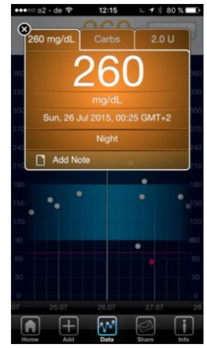

Figure 4 iBGStar Pop-up Cards

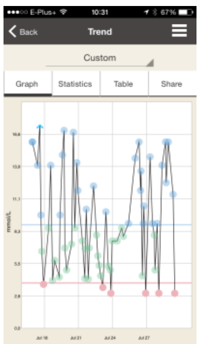

Figure 5 Accu-Chek Connected Plot

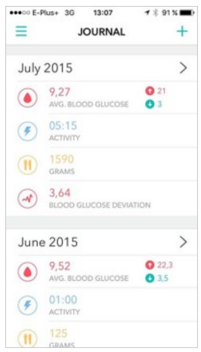

Figure 6 Diabetik Statistics

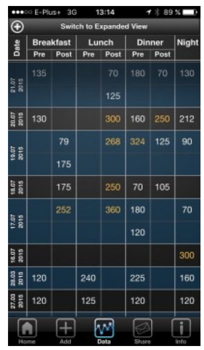

Figure 7 iBGStar Data Table

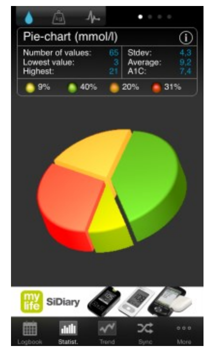

Figure 8 SiDiary Pie Chart

Daily Logbook with Connected Plot (Fig. 2)

This interface combines a daily diary and a graph, which scroll together in unison. This appears to add value, and responses tended to be improved over the logbook alone. Still, underlying patterns across multiple days remained difficult to locate. This interface could be helpful for attaining a daily overview.

UI Benefits

Pairing the logbook with a graph enhanced the ability to understand the flow of data, and was in general better received than the diary alone. For example, P6 stated *"…this here is actually quite nice because you can see the graph…if you have the diabetes diary you don't have the distance between the points…just from time to time when you test …so that's actually better."* Such an overview could be useful for assessing a day, for example P5 reflected, *"If this was my day… I (would) immediately … see why this was a bad day…I didn't do proper therapy."*

UI Limitations

However, 8/12 participants who interacted with this interface noted that the benefits of this system were still limited by lack of support for understanding underlying patterns. P16 questioned the value for data analysis, *"…I like the option to kind of wander through your glucose levels and so you can easily see if it (there) were rough times or everything went well, but…(to) get a deeper understanding, I don't think it's really helpful for me."* And P11 expressed visual overload, *"it's just too much going on, there's no focus."* P3 drew attention to the limits of this interface for understanding connections across multiple days, "*it's not easy to compare two days, you have to always scroll up and down."* P3 also noted an inherent challenge in this paradigm, that the lack of screen space necessitates putting more contextual information in a submenu or slider, *"(it's) really annoying that you can only see more information if you click on it…so for analyzing, its really difficult to see what's going on in your day."*

Non-Connected Scatter Plot (Fig. 3)

Scatter plots are a common means of displaying time series data, however some participants found this UI overwhelming. This UI can give a general overview of control, but, recognizing patterns, time of day, or translating this overview into actionable information can be challenging.

UI Benefits

The primary use of this interface appears to be general retrospective assessment of frequency of in/out of range values and overview of deviation. When asked to reflect on the data, P11 observed, *"so again most of them were alright… but a lot of them were too high and some of them were too… low."* Some participants noted that this could help motivate their diabetes management, for example when asked what they would think if this was their graph, P6 said "*seeing this many high blood sugars, I'm thinking oh man you should do something, you have to change something.*"

UI Limitations

Despite some benefits, 10/13 participants who interacted with this interface expressed reservations. P9 noted that the lack of connecting lines between dots made it difficult to understand the time series relation between data points, *"the data ... difficult to put it together…without the lines, there's so many points of data. It's hard to distinguish the trends…"* And P4 noted, *"no, these dots don't tell me anything because they don't have a relation to the other dots."* P7 noted the lack of greater insights, "*to find out what to do, I would probably have to look at each individual data point and kind of aggregate the knowledge."* And P16 stated, *"(it's) not easy to extract what I think needs to be extracted..."* And understanding daily patterns was not well supported as P6 noted, *"...this system lacks the ability to easily view time of day."* In general, the lack of context seems to restrict the value for translating this collected data into actionable information. As stated by P8, *"there`s no context provided to explain why the value is that high, so I can`t draw any conclusions from it."* And P12 notes how viewing the red dots of out of range values can be discouraging, noting that the viewed values would be "*demotivating, because maybe I tried to do my best to have more green dots… I failed."*

Pop Up Cards (Fig. 4)

Pop-up cards received positive feedback for allowing primary interfaces to remain uncluttered while allowing on-demand access to additional contextual information. While accessing such additional data is needed to understand the cause and effect relationships that affect BG levels, placing such information into sub-systems appeared to create excessive cognitive load.

UI Benefits

Providing additional contextual information allows for in depth information, such as insulin dosages and exercise, without cluttering up the primary interface. P16 noted, *"actually I like that… because it looks …clean and if you want more data you can get it."*

UI Limitations

In terms of understanding individual entries, this system appeared serviceable. However, in the larger context of understanding the implications of data, the sub-system creates cognitive challenges. P8 noted, *"the entries are easy to understand… it`s pretty accessible, but the analysis isn't."* This is especially problematic in pattern recognition across multiple days, an essential aspect of self-management. P3 observed, *"...there's too much information. Too many numbers…and (to)… compare the number here above …I'll have to switch through...to compare…two dates."* And P9 observed, "*…it just makes it a lot more time-consuming. It's harder to process the data because…to ...get the information for everything that I need, (I have to) to go through each point individually…"* And P9 continued, *"...I feel…a little bit frustrated trying to figure out what I needed to do. Using this it seems like it would be a lot of work to get the information that I would want out of it."*

Connected Scatter Plot (Fig. 5)

Connecting data points on a graph appeared to increase readability by better conveying the sequential nature of events, and conveyed a general assessment of BG control. However, gaining more in-depth insights remained challenging, especially on a mobile device. While there are some benefits, this still appears to be a tool for general assessment rather than specific event decision support.

UI Benefits

Like the scatter plot, this visualization also gives a broad overview of glycemic stability. However relative to the non-connected plot, connecting the data points increases the ability to perceive the relationship between measurements. P8 observed, *"because the dots are connected…it (is) possible to see some kind of trend."* While such an overview could also suggest potential treatment improvements, as noted by P4 who suggested that this deviation could indicate the need to adjust insulin therapy, *"... this going up, going down, going up… cycle. I would say the (basal) insulin is not working well."* P9 also felt that while viewing such information could be stressful, it could also be beneficial, *"... it would be frustrating to see, but also a little bit empowering knowing that I could see what I needed to do to make it better."*

UI Limitations

The small screen on the iPhone 5s appeared to limit the value of this graph, especially in terms of labeling, determining time of day, and correlations. P16 noted, *"...we are always looking for parallels between times and values or accidents and value, it's really hard to tell because the screen is so small…"* P9 agreed, stating *"it's hard to tell where the times are, because this just listed on it on a … daily basis but I think that's probably just an issue it's dealing with it on such a small screen."* P9 concluded, *"I think it would be more useful on a computer than on the smartphone."* As P7 reported mixed impressions, stating *"this is cool stuff...you'd want to look at (it), but not on a daily basis, it would be kind of like if you want to reflect on the last week or the last month …"* P7 on observing the out of range values observed, "*I would feel pretty negative about fact that I had gone high and it probably a little bit confused about how to improve it…there's not really any indication about what to do to improve the situation I've definitely can see that it's bad but…"* and P5 similarly found the tool to have limited value, saying *"...just the graph doesn't really help…you just see the value. It's useless. (It) gives you that good day or a bad day feeling but…"* And P15 had a similar response, *"the only conclusion I can make is that I was six times too low and many times too high but I don't even see the day here…(it's) complicated."*

Statistics (Fig. 6)

Statistics allow a glanceable summary of time series data. Some participants noted this to be motivating through drawing attention to the need for greater attention to care. However, such numbers can be difficult to understand, or can hide important details.

UI Benefits

Statistics, especially when presented without visual clutter, can help alert users to important general tendencies. P11 commented on the Diabetik interface, *"…simple clean overview of your highs and lows…this gives you a first indication of if you have a problem."* P11 reflected on this interface, *"…the average seems to be a bit little bit too high and …21 times too high blood sugar. I would …look a little closer about the high blood sugar."* Having the time period clearly labeled seems to be important for some users. P7 was positive about this feature noting, "*I like how it was broken up into month summaries…"* And P15 noted that cumulative data could help with general goals for diabetes management, *"I will try to reduce …how many times for example I'm too low."* and P9 felt that seeing personal data as numbers instead of viewing the high points on a graph was less stressful, *"...sometimes …when I look at big, overarching trends they can be discouraging. But sometimes it also gives it makes me feel more empowered to change things…the fact that it has numbers, and the way that it has it laid out, instead of it being like ups and downs, and seeing all the things from the graph, it …doesn't make me feel as bad about it."*

UI Limitations

Yet for other participants, information presented this way were perceived as limited in utility. P15 suggested it would not provide sufficient actionable data to guide action, *"I mean somehow it's not enough...I want to see the reason…for example I need to see whether it was in the night, and if it was in the night…was it too low…or too high..."* P15, who holds a PhD in mathematics, also observed that average can be a misleading statistic,*"...so I definitely see how many times it was too high, (and) how many times it was too low and this is actually interesting information for me and of course the average blood sugar. But average is a complicated number. So, I don't know …how to interpret this average."* P16 also brought attention to the potential misleading nature of averages based on small numbers of data points, *"...it's not the average, but just the average based on those three four five tests I had that day, and that is actually wrong information."* For some users, statistics are challenging to apply, as P6 stated, "…*my goal range, my average, ok so I can see the average of my blood sugar at breakfast lunch dinner at bed time …it's too confusing for me."* The inclusion of standard deviation brought mixed responses. P5 was positive, "*I think that standard deviation is much more important than Hb1c* (a cumulative 3-month average of BG levels*) or overall … hypers* (elevated BG levels*) or hypos (*lowered BG levels*)."* However, for others these features offer limited real-world value. P1 stated, "*I don't think these are super helpful because they just aggregate a lot, and I don't know enough about statistics, and I don't know what do with that…I know what deviation is, but I have no idea how to relate it to the number of tests."*

Data Table (Fig. 7)

Data tables are an established form of interaction with diabetes information, a paradigm extended from the handwritten diary. Therefore, this form has the advantage of familiarity, and also provides the ability to view many days simultaneously. While some users were positive about this UI supporting quick overviews, others were either confused, or felt that such structures were not useful.

UI Benefits

Having many days of BG values in simultaneous view, especially when color-coded, allows for easy recognition of out of range values. P16 found this useful, noting *"for me it is much more structured, …I get first attracted to compare all the post breakfast entries, and at the first glance I see that they are too high, but I actually see the low ones, 50's and 60's they were out of my sight somehow."* Noticing such details could be important for adjusting insulin dosages, as the low BG values could argue against a general increase in morning insulin. In contrast, averages could hide such insights. P9 also expressed that such formats were useful, *"…It seems like to me you can get a holistic view of each day, seeing what your blood sugars were."* P16 noted that such data structuring was "*helpful and easier to understand right away…I can just compare the entries for a given time zone like what we have post-breakfast. I can easily compare (that) they are all too high for example…(to) change the dose or the meal."*

UI Limitations

Despite some benefits for trend discovery, the volume of data was cognitively challenging for some. P3 observed, *"I'm overwhelmed with numbers…if you look at (it) as a normal user and the first time you are confused and overwhelmed by information."* And P11 also found the format not especially helpful *"...it's (like) getting through (spread) sheets…it feels technical, you don't get an overview."* And P16 was critical that the format was poorly suited to her needs, *"what I don't like is what I always hate about log books. It's this breakfast, lunch, dinner, night thing, because my day is just not structured like this. I feel like I am supposed to have that given structure and I just feel I don't want to."* P15 found this paradigm although familiar, was not delivering needed added value, explaining *"...for me that is just a piece of paper…That is what my doctor wanted… he gave me a piece of paper with such a table and said okay now you can write it down…it is not useful at all."*

Pie Chart (Fig. 8)

The Pie Chart gives a quick sense of values in set ranges, and appeared to successfully impart a general assessment of distribution. However, it seems limited in its ability to support decisions. It might be a tool best reserved for occasional demonstration of a particular insight or observation.

UI Benefits

This interface was effective in communicating a general overview of how often the data was within certain glycemic ranges. P15 noted, *"ok, I definitely see what is the percentage of my desired range, where I want to be, and (how often I was) too low, and where I (was) too high or really too high…I see that only 37 percent is in my desired range, and I definitely sees that I'm too low too often."* And P6 could interpret this chart to suggest the need for modification in management, *"okay so … it tells me I have to improve something if every third test is high, really high blood sugar I have to do something. 20% is nearly ok, only 37% is okay, and I think it should be much more. So, I have to work to get my average value down."*

UI Limitations

Despite certain benefits, this chart lacks support for interpretation. P9 explained, *"the pie chart probably wouldn't help me make decisions, but it would probably help me just to understand how I'm doing in a general way."* And while P9 rated this interface as "easy" to understand, also stated that the *"utility of it is limited."* And P11, a professional designer had a strong negative response to pie charts in general, "…*I hate to look at pie charts, it makes me vomit. I really, really, hate it. So I wouldn't open the app and look at it. I think it's too ugly."*

DISCUSSION

Throughout the study we saw that these interfaces were for the most part capable of helping people reference data. Furthermore, participants were well aware of the meaning of these data points. In this sense, the usability of these UIs is reasonably successful. They are also well suited to giving broad overviews which can be helpful for assessing performance and for some users can be motivating. However, the communication in regard to self-management is largely implicit, depending on the user to interpret data. Explicit and specific actionable information is generally limited. Given the frequent demands of diabetes management, this study indicates the need for more actionable interfaces, that offer a cognitive load sweet point where useful knowledge is easier to acquire, while still keeping users mentally engaged with their data. We suggest better filters could be offered to help users sift through data or specific contextual clues which could indicate where to focus attention. In addition, there are indications that excessive focus on past data is not well suited to user's actual needs for situated decision making, and can place emotional strain in some circumstances.

Three Questions for Designers of Mobile Health Apps

In the previous sections we selected quotes, to draw attention to benefits and shortcomings of specific UI paradigms in relation to user interaction with a sample diabetes relevant data set. We drew attention specifically to two areas, cognitive and affective challenges. In the following three sections, we identify unresolved design issues for designers of diabetes self-management apps that our analysis reveals. The first two sections relating to the cognitive and affective challenges, and a third more general question related to accessing the extensive self-care knowledge shown by our participants. For each section, we identify: an open question raised by the study; current approaches; problems or shortcomings; challenges; and possible directions in which answers might lie. By evidencing each of these areas of concern and by identifying those that seem to have most impact on users of health apps for diabetes, we hope to draw attention to the potential for improvement of well-accepted UI paradigms in this area, and to emphasize the importance of finding new approaches for health app interaction design.

1. Improving Interaction with Data

How can we design engaging UIs that lower the cognitive demand associated with interacting and deriving value from complex data?

Shortcomings

There was a relatively low adoption of these technologies among our participants, despite a majority of individuals reporting technological skills and interest in diabetes products. It did not appear that the positive aspects of the interfaces created sufficient enthusiasm to encourage active and frequent engagement. As P11 said, such interfaces are like *"filling out an Excel spread sheet for the rest of my life."* While it might be thought that increasing automation of data collection could ameliorate this problem, the study suggested that these standard data visualizations can create confusion and cognitive overload for even educated, and technology adept users. For example, information presented on multiple screens or hidden on sliders, created excess cognitive load. P3 noted how difficult it was to compare information across multiple days if it was not simultaneously visible. Such limitations suggest that increased automation will not cause these apps to provide adequate support for utilizing collected data, without rethinking the general assumptions of these visual paradigms.

Current Approaches

The apps in the study used widely accepted methods for visualizing data. In many cases, participants felt that the described interfaces could assist in gaining overviews, and informing management decisions. The *plotted graphs*, especially with connected dots, were successful in communicating frequency of test within certain ranges, and gave an overview of variation. For example, P4 noted how such extreme variation could be indicative of the long-acting insulin needing adjustment to smooth deviation. *Statistics, and pie charts* were appreciated for giving benchmarks for performance, with P11 noting how such overviews could give a clear indication of problems that needed to be addressed. *Data tables*, especially when color-coded, allowed quick overview of multiple days, and could help to detect obvious patterns, such as sequential elevated morning glucose levels. P9 noted that such structures helped with getting a quick overview of a day.

Challenges

Parts of this first design challenge is neither new nor original, but, given continued acceptance and application of these visual techniques and the evidence presented, we believe it is critical that new methods be explored, especially in regard to multivariate data. As noted previously [23], care must be taken in development to assure that such interfaces challenge rather than confirm biases. In the case of health apps in general, and diabetes apps in particular, designers need to consider the challenge of reducing the cognitive demands of interacting with complex data in the context of usage requirements, such as: high frequency; short time periods; varied contexts of use; emotional sensitivity (see next section), and lack of situated professional assistance.

Potential Paths Forward

One simple but often overlooked and underexplored visualization technique is to offer a tilted arrow showing trends (first derivative) over appropriate time scales. This approach fits well with regular automated data collection. For example, the home UI on the Abbott Libre supplements standard display elements such as current BG level, and graph of BG over time, with a vector arrow showing current rate and direction of BG change. This interface element is compelling, allowing for practical and glanceable situated advice. We encourage exploration in departing from conventional graphs and charts as standard daily management tools, in favor of simpler and more intuitive approaches.

2. Emotional Sensitivity

How can we design emotionally sensitive interfaces that draw attention to important but unwelcome information while continuing to engage the user?

Shortcomings

Collected health data can have an affective aspect that must be carefully considered when designing UIs. Alerting the user to urgent information, such as a dangerously out of range BG values, must be balanced with maintaining long-term engagement and not causing undue stress. As P16 recalls about their experience using a diabetes app *"it's nice when your blood glucose levels are under control, but once it's not… the app doesn't help you, and…I (got) more frustrated by the messages and the designs…"* When PwDs are having a difficult time controlling BG levels, they can feel vulnerable, and being confronted with this perceived failure can be counterproductive.

Current Approaches

One approach in diabetes apps is gamification, for example the use of an animated 'monster' in the popular app mySugr. However, such approaches can be self-defeating. For example, P16 felt the monster trivialized disease management, stating, *"I'm an adult, and I feel treated like a child."* Or P11 who commented on the same app's sound effects, *"I really hate the sound… it's just too playful for me."* The Akku-Chek app, chose to use blue for elevated BG levels, rather than the more conventional red, which was perceived positively by P12 who remarked that they liked having this color scheme as it reduced stress.

Design Challenges

Due to variations in personality, it is not clear that there are universal solutions when it comes to affective requirements. For example, while P9 noted how seeing numbers instead of out of range points reduced stress, P15 drew attention to how having their life reduced to a continuous set of numbers created a sense of burden. Similarly, while P12 noted how viewing red dots could have a demotivating effect on diabetes management, P7 observed, *" I don't really know why the high numbers are blue because… blue seems like a good thing to me."* As out of range BG values not only demand immediate attention, but are also a constant reminder of long-term risks and failure to maintain adequate control, there are diverse factors to be balanced. Examples include variation in personalities, contexts, and, levels of urgency.

Potential Paths Forward

It is vital that user tests be carried out not only with 'good' data, but also with 'bad' data, which is to say data that reflects undesired states. However, different users have different goal ranges, which can vary according to context. For example, P4 noted *"I need to put my blood sugar at 250 (mg/dL) when I'm working because I don't want to (have) low sugar on machines."* This highlights the importance of clarity about care targets for different individuals in different contexts, not just in interaction design but also when personalizing data for testing purposes. The importance of variation in individual preferences might suggest the need for adaptive interfaces or better options of customization. While this is a perennial topic of research [3], it is largely unexplored in the present context.

3. Triggering Acquired Knowledge

How do we design UIs that trigger the user's acquired knowledge at the appropriate time?

Shortcomings

Throughout the study, participants drew upon their already acquired and often extensive knowledge as they sought to make sense of the data. For example, P1 noted that a low BG was probably caused by exercise, before looking for confirmation. Similarly, P4 suggested that a high BG level could have been caused by an insulin dose that was supposed to last 24 hours, but, in her experience, due to shorter actual action, is best administered in split dosages so as to not leave gaps in coverage. Such examples lend support to Mamykina's *sensemaking* theory: such a catalog of easily accessible self-care models allows for practical and sustainable management. However, the findings suggest that it is far from easy to recognize when relevant knowledge could be applied to a data pattern, and this could be even more difficult when users are under common pressures such as cognitive, affective, attention, or time. The key shortcoming here is simply that none of the representative health apps appears to directly address this problem.

Current Approaches

Some apps, such as mySugr, include contextual tags paired with icons for common factors that can affect BG levels, such as manual work, sickness, or travelling. However, these are entirely dependent on the user's motivation to participate in extensive logging and effortful reflection.

Design Challenge

In a slight modification of [16], we need to find ways to help *trigger the right model, at the right time, in the right way*. Due to the off-putting drudgery (for many) of maintaining continual diaries, acquisition and delivery of such information needs to reduce manual input from the user.

Potential Paths Forward

It appears that systems able to meet such challenges will need to learn about the individual user, and what specific knowledge they must access in a given context. One possible starting point is the work of [28] on *'tool-effect-modeling'*, which proposes a system that correlates sensed behaviors with desired outcomes. Once these connections have been established, they can then be used to create an anticipatory positive feedback loop. Thereby encouraging the personal and specific behaviors that have been previously beneficial. While this appears a compelling approach, care must be taken to not trigger incorrect models, which could bring about harmful actions. Also careful attention must be taken as to the nature of this human machine relationship: [27] is an insightful paper on this subject. Other relevant work includes [8] on ranking behavior impact factors, and [12] for work on glanceable displays that provoke the user to ask meaningful questions rather relying on a system supplying explicit answers.

LIMITATIONS

As noted previously, participants did not reflect on their own personal data, which through greater familiarity and attached memories could have increased insight extraction. We welcome other researchers repeating this experiment with participant's personal data to examine how this might influence interaction and add additional insights. The approach to recruitment may have led to a non-representative overly technically literate and early-adopter group. This may have biased findings towards the success of the technology; however, the many challenges encountered by this group might suggest even more problems with less technologically literate users. Many apps tested (5/6) used mmol/L as units for stored BG values, while some users were only familiar with mg/dl. While they were instructed as to the conversion factor and provided with a conversion sheet, this might have decreased performance.

CONCLUSIONS

Sessions with 16 users interacting with representative UI designs for diabetes self-help apps have been analyzed to see how well they meet users' needs. We have drawn attention to two principal areas of failure: excessive cognitive demands on users to extract value; and the need for emotional sensitivity given the affective potential of these interactions. Cognitively, these apps require too much effort to make sense of data and locate meaningful insights, exposing users to visual confusion and cognitive overload. Emotionally, the complex relationship users have with their data appears inadequately considered. We have also proposed 3 questions for designers to advance these tools so that they can serve a more meaningful role in people's lives.

If the purpose of such apps is variously: to provide a digital tool for periodic troubleshooting of specific problems; recording diverse data for interaction with a health care provider; and to give the patient broad overviews of collected data; then one may consider these apps tolerably successful. Our participants were generally comfortable browsing through and understanding the significance of individual data entries, and in most instances, given a little time for close examination, could understand data within graphs and charts. Yet, as this study has illustrated, users' day-to-day needs appear somewhat different. We have presented evidence from the literature that the majority of diabetes care is self-care, and that patients should be enabled to independently make frequent well-informed care decisions. Based on these premises, the current study gives evidence that current diabetes apps are inadequate for such goals. Given the number of apps based on a narrow range of interaction and UI paradigms, one must ask why so many app developers continue to deliver apps that fail to adequately address users' problems, require significant daily effort to assemble representative data, show debatable improvements in outcomes, and have low adoption rates.

While the desire to avoid medical regulation is a factor, perhaps it is also because they adhere to a model that is too closely tied to clinical requirements and conventions that focus on a mediated session, and thereby are ill suited to actual user requirements and expectations. We posit that this is not just a matter of adding new ways for patients to record more data, automation of data entry alone, more attractive color schemes, or even more visually appealing designs and interactions. Rather there is a need to reconsider how to help users draw value from real and often noisy diabetes data. Furthermore, there must be realistic assessment of available cognitive expenditure and emotional resilience given the contexts and frequency of usage.

In summary, despite some tangible benefits from these UIs, we appear to have a widespread and repeated failure to understand user requirements combined with a lack of willingness to challenge established conventions. We suggest that the three posed questions should be answered so that we can move towards more effective and sensitive systems for health management.

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